Toward low cost smart agriculture monitoring system using IoT and remote sensing

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Abstract- As the world population increases, our food production capacity must also increase to provide enough food. Empowering smallholder farmers, with low-cost but efficient tools to reduce cost and boost yield, is important for future food security. Presently, there are many IoT-based tools helping farmers to monitor farms. Some research suggests inexpensive components to reduce the cost of hardware; to make these tools affordable for smallholder farmers, who contribute a third of the world's food. We propose replacing some hardware sensor functions with software solutions like satellite data combined with data science technologies to minimize the number of sensors used to monitor farm conditions. After cleaning data collected from a farm, we build models that predict sensor values, and we compare the models by accuracy, time and space complexity. This solution is effective for a wide variety of crops like paddy rice, fruits and vegetables, and for open-air or indoor cultivation.

Index Terms- Internet of Things, Precision Agriculture, Artificial Intelligence, Multispectral analysis.

I. INTRODUCTION

The United Nations projects the population of the world to reach 9.7 billion people by the year 2050, and 10.4 billion by the year 2080 [1]. The projected rise in population necessitates an increase in food supply, in order to feed the population sufficiently. To prevent accelerating soil erosion and worsening climate conditions, this increase in food supply must be achieved with great care [2]. This means, instead of simply using more land and water to produce more food, it is necessary to investigate how to use these resources efficiently to raise production capacity in relation to resources consumed.
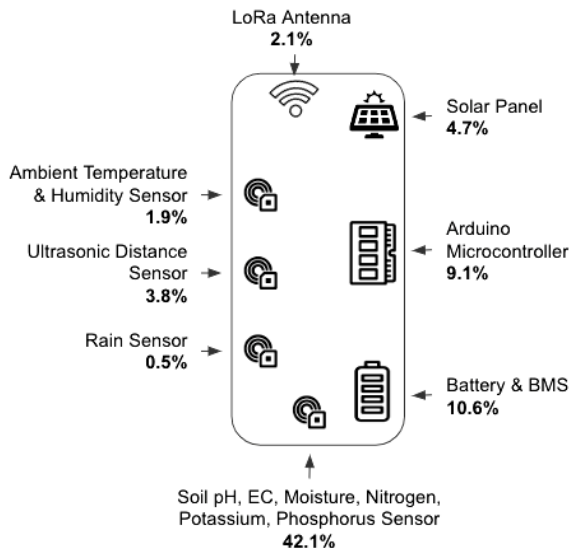

Fig. 1. Cost distribution of main components of sensor module.

This research is an ongoing study aimed at lowering the cost of the Smart Agriculture Monitoring System (SAMS) designed and implemented in an earlier stage of the research. We investigate the possibility of lowering the cost of the SAMS by replacing hardware components with software solutions. The SAMS monitors atmospheric conditions including temperature, humidity, precipitation, and sunshine intensity. It also monitors temperature, moisture, electrical conductivity, pH, nitrogen, potassium, and phosphorus in the soil.

The SAMS comprises of sensor modules that collects and sends farm data to an edge device. Figure 1 shows the sensor module with the cost factors of the main components. The soil sensor and the ambient temperature and humidity sensor constitute 44% of the estimated cost. Replacing them with data and software alternatives will substantially reduce the cost of the sensor module.

II. RELATED WORK

Increasing crop yields to feed the expanding world population and reducing greenhouse gas emissions to combat climate change are two stresses that agricultural ecosystems must contend with [3]. To reduce the cost of IoT solutions to make them affordable for smallholder farmers, some researchers suggest the use of low cost components [4], [5]. Other research works have investigated measuring vegetation metrics with Multispectral Satellite Data (MSD) [6], [7]. In this research we investigate the use of data and software alternatives to replace hardware components to reduce the cost of sensor modules, to reduce the number of sensors. We use MSD and open weather data with data science technologies to predict atmospheric and soil conditions.

III. MATERIALS AND METHODS

In this research, we explore the use of open satellite data (for atmospheric temperature, humidity, precipitation and sunlight intensity) and MSD in combination with data science technologies to predict atmospheric and soil conditions, in replacement of the corresponding hardware sensor components. Data of atmospheric and soil conditions collected with the initial version of the system, from the earlier research, will be predicted from open weather data and MSD. Atmospheric and soil conditions were monitored with sensors in the farm.

Our SAMS was deployed in a paddy rice field in Aso, Kumamoto Prefecture in Japan for 4 months during the cultivation period, where data was collected for ambient temperature, humidity, sunlight intensity (inferred from solar

panel voltage), soil temperature, soil moisture, water level above the soil (height of flood), electrical conductivity of soil, nitrogen, potassium and phosphorus in the soil. We cleaned the data by removing erroneous values like temperature values above 60 degrees Celsius, since the highest ambient temperature ever reported in history does not exceed 60 degrees Celsius. We also removed out layers like instantaneous spikes in humidity and soil temperature, since such properties only change gradually in the real world. We treated these erroneous data as missing values and replaced them with the K-nearest Neighbor imputation.

In the next phase of this research, data from Meteostat.net (a provider of free historical weather data) for ambient temperature, humidity, sunlight intensity and rain state, will be compared with sensor data collected. MSD will be collected from Sentinel Hub and USGS EarthExplorer for the period of time corresponding to the data collection period. The frequency distribution of pixel intensities (infrared signature) of different frequency bands of the MSD will be used to train an Artificial Neural Network to predict the soil temperature, moisture, pH, Electrical Conductivity (EC), nitrogen, potassium and phosphorus levels of the soil.
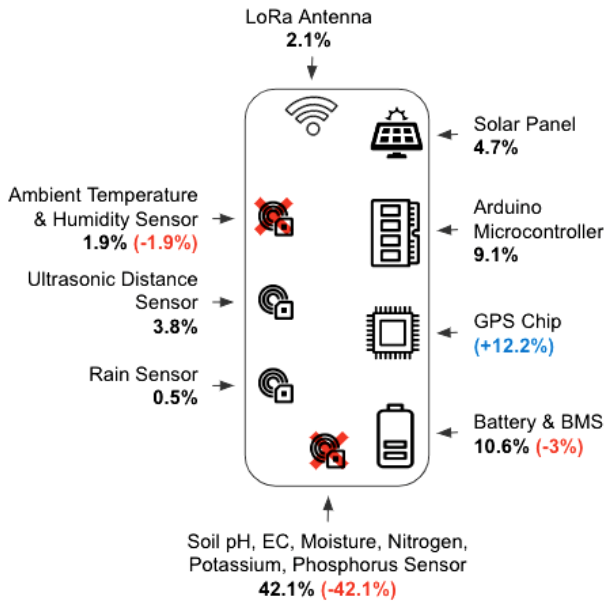

Fig. 2. Cost distribution of main components of sensor module after modification.

IV. RESULTS AND DISCUSSION

Our initial exploratory data analysis revealed trends and high correlation of soil moisture and electrical conductivity with the measure of nitrogen, potassium and phosphorus in the soil, agreeing with related literature. We also found high correlation between ambient temperature, humidity and sunlight intensity, also agreeing with literature.

Training ANN with MSD to predict soil properties is expected to achieve satisfactory results, because MSD is known to have representation of physical and chemical characteristics of vegetation and soil [7], [8], and data science technologies have shown success in analyzing MSD [7].

The replacement of atmospheric and soil sensors, directly lead to the reduction of the cost of the module, since the alternatives are free. Also, the total number of messages to be sent through the radio to the edge device also reduces substantially. As a result, the required battery capacity and solar panel ratings are lowered to reduce the module cost.

For improved usability, a GPS chip will be added to the sensor module to automate the location plotting in the MSD. This will introduce an estimated increase in cost of 12% of the sensor module. Figure 2 shows the cost distribution of the main components of the sensor module after modification.

It worth noting that the use of MSD means the sensitivity of the system will depend on the update frequency of the MSD. MSD update frequencies range from hourly to daily. In the worst case of daily MSD updates, changes in farm conditions may be reported after a day.

V. CONCLUSION

The successful replacement of hardware sensor components with software alternatives is expected to reduce the cost of the sensor module of the SAMS by over 30%.

The reduction in cost of the sensor module is as a result of 1) the elimination of atmospheric sensors for temperature and humidity, 2) the elimination of soil sensors for temperature, moisture, electrical conductivity, pH, nitrogen, potassium and phosphorus, 3) the substantial reduction of required battery capacity, and 4) the substantial reduction in the required capacity of the solar panel.

VI. REFERENCES

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